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Explainable Labor Market Intelligence from Online Job Postings: Multi-Frequency Skill Demand Monitoring and Forecasting

ahmad adi

ahmadcahyonoadi@mail.ugm.ac.id

Universitas Gadjah Mada

Mona Anjali Bire

Padjadjaran University

Brigita Bowaire

Binus University

La Fajrin

Universitas Gadjah Mada

Lod Insyur

IPB University

Maria Florensia Lay

Padjadjaran University

Muhamad Mubarok

Padjadjaran University

Fajar Muhammad

Padjadjaran University

Dara Muliyani

Padjadjaran University

Nilam Rostyana

Padjadjaran University

Jarwoko Saputro

Universitas Gadjah Mada

Krishna Setiadi

Padjadjaran University

Chaterina Suweni

Diponegoro University

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Explainable Labor Market Intelligence from Online Job Postings: Multi-Frequency Skill Demand Monitoring and Forecasting

Abstract

Rapid digital transformation and artificial intelligence diffusion have intensified the need for timely and interpretable labor market intelligence. While online job postings provide rich real-time signals of employer demand, existing studies often emphasize predictive accuracy while offering limited insight into the persistence, volatility, and strategic meaning of skill demand dynamics. To address this limitation, this study proposes an Explainable Labor Market Intelligence framework that transforms large-scale online job postings into actionable workforce planning signals. Using more than 124,000 LinkedIn job postings from December 2023 to April 2024, the proposed framework constructs Weekly Skill Demand Indices and applies Empirical Mode Decomposition to separate short-term fluctuations from structural trends. Multi-Frequency Hurst Analysis identifies persistent skill demand patterns ($H > 0.5$), while XGBoost forecasting models achieve $R^2 = 0.386$ in predicting aggregate demand changes. SHAP-based explainability reveals that recent demand momentum and short-term trends are the primary drivers of forecasted changes. The framework generates actionable intelligence signals, identifying healthcare ($H = 0.937$) and management ($H = 0.783$) as persistent emerging skills, while information technology ($H = 0.825$) and sales ($H = 0.626$) show declining trajectories despite persistent behavior. By integrating skill extraction, persistence analysis, explainable forecasting, and intelligence generation, this study bridges the gap between large-scale online job posting analytics and strategic workforce decision-making, offering marketing analysts and HR strategists an interpretable tool for proactive talent management.

Keywords: Labor Market Intelligence; Skill Demand Forecasting; Online Job Postings; Workforce Analytics; Multi-Frequency Analysis; Explainable AI; SHAP; Strategic Workforce Planning

1 Introduction

The contemporary labor market is undergoing rapid structural transformation driven by digitalization, automation, artificial intelligence, and the growing reconfiguration of organizational skill requirements [1–3]. These changes have intensified uncertainty for employers, educational institutions, policymakers, and workforce planners. In such

an environment, the ability to identify emerging skill demand, monitor occupational shifts, and anticipate future workforce needs has become a strategic requirement rather than a purely statistical exercise. Traditional labor market statistics, while reliable and institutionally standardized, are often released with temporal delays and may not fully capture fast-moving changes in employer demand. As a result, researchers and practitioners have increasingly turned to online job postings as a real-time source of labor market information, serving as early labor market signals [4, 5].

Online job postings offer granular and timely evidence of employer demand. Unlike aggregate labor statistics, job postings contain detailed information on job titles, descriptions, required skills, salary ranges, locations, employment types, industries, and company-level characteristics. These attributes make online job postings a valuable data source for constructing labor market intelligence systems. Through large-scale analysis of job advertisements, it becomes possible to observe not only how many workers are demanded, but also what types of skills, competencies, and occupations are becoming more or less important over time.

The growing availability of online job posting data has created new opportunities for workforce analytics and strategic planning. Employers can use skill demand signals to adjust talent acquisition strategies, educational institutions can align curricula with evolving market requirements, and policymakers can identify areas where reskilling or upskilling interventions are needed. The strategic integration of predictive analytics—a methodology highly refined in digital marketing and e-commerce to analyze consumer behavior, digital market power, and relationship retention [6–9]—is now being actively adapted for human capital and workforce survival analysis. Educational institutions, for instance, are increasingly reliant on data-driven recommendation systems to align higher education trajectories and student employability with evolving industry requirements [10, 11]. However, converting raw job posting data into actionable labor market intelligence remains challenging. Job descriptions are often unstructured, noisy, heterogeneous, and written using inconsistent terminology. Furthermore, observed labor demand series may contain a mixture of short-term fluctuations, seasonal patterns, and trend persistence. Forecasting such demand without distinguishing between transient and persistent dynamics may lead to misleading conclusions.

Existing labor market forecasting studies have made important methodological advances by applying machine learning, deep learning, and natural language processing to employment data and job postings [12–14]. Nevertheless, three important gaps remain. First, many studies focus primarily on predictive accuracy and provide limited interpretation of how forecasting outputs support workforce planning or labor market intelligence. Second, labor demand is frequently modeled as a single aggregate time series, even though skill demand may exhibit multi-frequency behavior involving short-term shocks, cyclical changes, and demand continuity. Third, many forecasting models operate as black boxes, limiting their usefulness for decision-makers who require transparent explanations before adopting model-generated recommendations.

This study proposes an Explainable Labor Market Intelligence framework for skill demand monitoring and forecasting using online job postings. The framework integrates skill extraction, Weekly Skill Demand Index construction, multi-frequency decomposition, Hurst-based persistence analysis, explainable forecasting, and labor

market intelligence generation. Instead of treating forecasting as an end in itself, this study positions forecasting as a decision-support tool for transforming online job postings into actionable insights regarding emerging, persistent, and declining skill demand.

The proposed framework is evaluated using the LinkedIn Job Postings dataset, which contains more than 124,000 job advertisements from December 2023 to April 2024. This dataset provides a rich source of information on job titles, descriptions, companies, salaries, locations, and employment characteristics. By extracting skill signals from job postings and aggregating them into weekly indices, this study develops a structured representation of employer demand. These indices are then decomposed using Empirical Mode Decomposition (EMD), analyzed using Multi-Frequency Hurst Analysis, and forecasted using XGBoost. SHAP explainability is incorporated to identify the features and demand components driving model predictions.

This study addresses four research questions:

- **RQ1:** Do skill demand dynamics exhibit persistent behavior and demand continuity that can be quantified using Hurst exponent analysis?
- **RQ2:** Can multi-frequency decomposition improve the interpretability of labor market intelligence by separating transient fluctuations from structural trends?
- **RQ3:** Can explainable forecasting models identify the key drivers of skill demand changes and provide transparent decision support?
- **RQ4:** Can skill demand forecasting be transformed into actionable workforce intelligence categories that support strategic planning?

This study makes three main contributions. First, it contributes to labor market intelligence literature by demonstrating how online job postings can be transformed into interpretable skill demand signals with weekly temporal resolution, serving as early labor market signals. Second, it contributes methodologically by integrating multi-frequency decomposition, Hurst-based persistence analysis, and explainable machine learning within a unified forecasting framework. Third, it contributes practically by generating workforce intelligence outputs that can support strategic workforce planning, educational alignment, reskilling initiatives, and talent acquisition decisions.

2 Related Work and Theoretical Background

Labor Market Intelligence (LMI) refers to the systematic collection, processing, analysis, and interpretation of labor market data to support employment-related decision-making. Traditionally, LMI has relied on official statistics such as employment rates, unemployment rates, vacancy counts, wage data, and occupational projections. While these indicators remain valuable, they are often limited by reporting delays and may not reflect real-time shifts in employer demand. The emergence of online job boards and professional recruitment platforms has expanded the scope of labor market intelligence. Online job postings provide detailed employer-side information about occupational demand, skill requirements, salary expectations, geographic distribution, and industry-specific hiring patterns. As a result, job posting analytics has become increasingly important for workforce planning, recruitment strategy, and policy analysis,

particularly through data-driven database processing and information standardization [15, 16]. Workforce analytics extends this perspective by using data-driven methods to support decisions related to human capital planning, talent supply, skill gaps, and organizational capability development. Within this context, forecasting labor demand is not merely a statistical problem but a strategic planning problem. Organizations and policymakers need interpretable insights into which skills are emerging, which skills are persistent, and which skills are declining. Therefore, labor market forecasting must evolve into labor market intelligence.

Skill demand forecasting focuses on estimating future employer demand for specific competencies, tools, technologies, and capabilities. Online job postings are especially useful for this task because they contain direct textual evidence of required skills. Prior studies have used job advertisements to identify demand for digital skills, technical skills, management skills, soft skills, and industry-specific competencies through hierarchical occupational classification [17], job title identification [18], and continuous skill taxonomy adaptation [19]. However, extracting reliable skill demand signals from job postings presents several challenges. Job descriptions are often unstructured and inconsistent across employers, different companies may refer to the same skill using different terms, and skill demand can vary across time, location, industry, and occupation. Furthermore, job posting counts may be affected by short-term hiring campaigns, seasonal effects, and labor market shocks. These challenges suggest that skill demand forecasting requires more than simple frequency counting. Unsupervised learning methods have similarly provided structural insights into the evolution of labor markets, enabling researchers to cluster shifting occupational behaviors over different economic periods [20]. Furthermore, machine learning explorations have been instrumental in assessing the localized impacts of global macroeconomic shocks, such as the COVID-19 pandemic, on vulnerable and older-age worker cohorts [21]. To operationalize these predictive models in human resources and workforce analytics, organizations are increasingly deploying SQL-driven data pipelines and interactive business intelligence dashboards, transforming raw algorithms into tangible, quantitative decision-support systems [22]. Crucially, this advanced text processing facilitates the extraction of tacit knowledge—implicit industry signals, semantic skill clusters, and shifting operational behaviors—that traditional analytics fail to capture, thereby enriching comparative labor market forecasting [23].

Labor markets are not purely random systems. Employer demand may exhibit persistence due to technological diffusion, structural industry transformation, regulatory changes, demographic pressures, and long-term organizational investment in specific capabilities. At the same time, labor demand may also contain short-term fluctuations driven by seasonal hiring, business cycles, economic uncertainty, or temporary market shocks [24–26]. The Hurst exponent provides a useful measure for identifying persistence in time series, distinguishing structural trends from random walks and market efficiency [27]. A Hurst exponent greater than 0.5 indicates persistent behavior, suggesting that increases in demand are likely to be followed by further increases. A value close to 0.5 indicates behavior similar to a random walk, while a value below 0.5 indicates anti-persistent dynamics, where increases are likely to be followed by reversals [28, 29]. However, aggregate labor demand series may contain multiple temporal

structures. Short-term components may behave differently from long-term components. Therefore, estimating persistence on the original series alone may obscure important multi-frequency dynamics. Studies utilizing multifractal detrended fluctuation analysis (MF-DFA), wavelet coherence, and polyspectral mean-based clustering have successfully uncovered the switching impacts of policy uncertainty, pandemic disruptions, and trend persistence on market efficiency [30–32]. To bridge the gap between fractal market structures and predictive accuracy, hybrid architectures such as fractional neuro-sequential models and fractional Ornstein-Uhlenbeck processes have been engineered, alongside advanced mathematical modeling techniques adapted from other fields like interval inversion [33–35]. Furthermore, the integration of external sentiment data has proven vital. For example, extracting media news sentiment via Bidirectional LSTM networks serves as a powerful leading indicator of labor market fluctuations when integrated into theoretical frameworks such as the DMP model [36].

As machine learning models become increasingly used in labor market analytics, explainability becomes critical. Forecasting models may provide accurate predictions, but decision-makers also need to understand why a specific skill is predicted to increase or decline. Without interpretability, model outputs may be difficult to trust, audit, or translate into strategic action. Responsible AI frameworks and weak signal detection mechanisms are emerging as critical requirements to ensure that algorithmic labor market forecasting remains transparent, equitable, and capable of supporting proactive, strategic policymaking [37, 38]. Explainable AI methods such as SHAP (SHapley Additive exPlanations) provide a way to interpret model predictions by assigning contribution values to input features, helping transform forecasting models from black-box prediction tools into transparent labor market intelligence systems.

The theoretical foundation of this study is built upon a cohesive thread connecting *Labor Market Intelligence Theory*, *Digital Labor Market Analytics*, and *Explainable Workforce Analytics*. First, *Labor Market Intelligence Theory* posits that organizations gain competitive advantage by systematically gathering, analyzing, and acting on market information, which in the digital age extends to real-time labor market signals. Second, *Digital Labor Market Analytics* provides the methodological basis for extracting these signals from unstructured data, positing that online job postings serve as high-fidelity proxies for organizational demand and early labor market signals. Third, *Explainable Workforce Analytics* argues that for predictive models to drive strategic decisions, they must transition from opaque systems to interpretable frameworks. This study grounds its approach in this thread, ensuring that algorithmic outputs are not just statistically accurate, but strategically auditable and actionable.

Despite the methodological advancements in job posting analytics and machine learning forecasting, a critical research gap remains in the marketing and analytics literature. Existing studies predominantly treat labor market forecasting as a purely predictive engineering task, focusing on minimizing error metrics (e.g., RMSE, MAE) while neglecting the strategic interpretability required by practitioners. Furthermore, current approaches rarely distinguish between transient market noise and structural demand shifts, leading to reactive rather than proactive workforce planning. This study explicitly addresses this gap and contributes to the existing body of knowledge in three distinct ways. First, it contributes methodologically by integrating multi-frequency

decomposition with explainable AI, shifting the paradigm from mere *predictive accuracy* to *strategic interpretability*. Second, it contributes theoretically by operationalizing Digital Labor Market Analytics and Explainable Workforce Analytics into a unified framework that transforms raw, unstructured data into theory-grounded workforce intelligence. Third, it contributes practically to marketing and HR analytics by generating actionable intelligence categories (Emerging, Persistent, Volatile, Declining) that directly support strategic resource allocation, curriculum design, and talent acquisition decisions.

Table 1 Positioning of the Proposed Study within Existing Labor Market Analytics Research

Research Stream	**Data Source**	**Objective**	**Limitation**	**Our Contribution**
Traditional Labor Forecasting	Official labor statistics	Forecast employment trends	Limited granularity and reporting delays	Real-time skill demand monitoring using online job postings.
Job Posting Analytics	Online job advertisements	Extract occupations and skills	Primarily descriptive analysis	Forecast-ready skill demand indices with temporal aggregation.
Machine Learning Forecasting	Labor market indicators	Improve prediction accuracy	Limited interpretability	Explainable forecasting using XGBoost and SHAP.
Persistence Analysis	Financial and economic time series	Detect market memory	Rarely applied to labor demand	Multi-frequency persistence analysis of skill demand dynamics.
Explainable Analytics	Model predictions	Interpret black-box models	Limited decision-support perspective	Actionable labor market intelligence generation.

As summarized in Table 1, existing studies tend to focus on isolated aspects of labor market analytics. Traditional forecasting emphasizes aggregate employment trends, job posting analytics emphasizes descriptive skill extraction, machine learning studies emphasize predictive accuracy, and explainable AI studies emphasize model transparency. However, few studies integrate these elements into a unified labor

market intelligence framework. This study addresses this gap by combining online job posting analytics, weekly skill demand indexing, multi-frequency persistence analysis, explainable forecasting, and strategic intelligence generation.

3 Proposed Method

This section presents the proposed Explainable Labor Market Intelligence (LMI) framework in comprehensive detail. The framework is designed to transform large-scale, unstructured online job postings into interpretable, multi-frequency, and actionable skill demand forecasts. Unlike conventional forecasting approaches that focus solely on predictive accuracy, the proposed framework emphasizes the generation of strategic labor market intelligence for workforce planning, educational alignment, reskilling strategy, and talent acquisition decision-making.

3.1 Framework Overview and Data Processing

The proposed framework operates through seven interconnected, sequential stages, transforming raw textual data into strategic intelligence:

1. **Data Acquisition and Preprocessing:** Cleaning and standardizing raw job posting text using Natural Language Processing (NLP) techniques including lowercasing, HTML tag removal, tokenization, stop-word elimination, and lemmatization.
2. **Skill Extraction and Standardization:** Mapping unstructured text to a standardized skill taxonomy derived from the dataset's supplemental skill files and enriched using established labor market taxonomies.
3. **Weekly Skill Demand Index (SDI) Construction:** Aggregating skill mentions into normalized weekly time-series data to capture rapid labor market dynamics.
4. **Multi-Frequency Decomposition (EMD):** Separating the SDI time series into Intrinsic Mode Functions (IMFs) representing different temporal frequencies and a residual trend component.
5. **Multi-Frequency Hurst Analysis:** Quantifying the persistence ($H > 0.5$), anti-persistence ($H < 0.5$), or random-walk behavior ($H \approx 0.5$) of each decomposed component using Rescaled Range (R/S) Analysis.
6. **Explainable Forecasting (XGBoost + SHAP):** Predicting future demand changes using gradient boosting and attributing predictions to specific features using SHAP values.
7. **LMI Generation:** Synthesizing outputs into actionable categories (Emerging, Persistent, Volatile, Declining) based on growth rates, Hurst exponents, and forecast directions.

The overall data flow is mathematically and logically summarized in Figure 1, illustrating how raw textual inputs are progressively structured, decomposed, and interpreted.

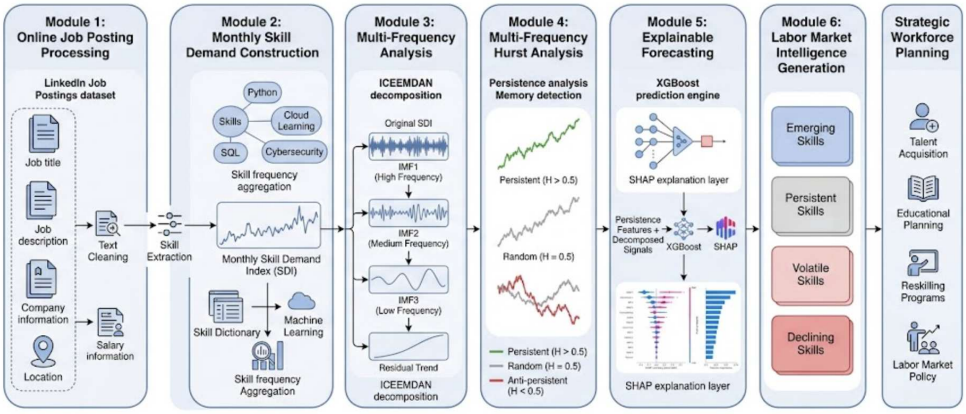


Fig. 1 Overall architecture of the proposed Explainable Labor Market Intelligence framework. The pipeline flows from raw unstructured job postings through NLP preprocessing, multi-frequency decomposition (EMD), persistence analysis (Hurst), and explainable forecasting (XGBoost + SHAP) to generate actionable workforce intelligence.

3.2 Data Source and Skill Demand Index Construction

The empirical analysis utilizes the LinkedIn Job Postings dataset, comprising more than 124,000 job advertisements collected globally during the period from December 2023 to April 2024. Each posting contains rich, multi-modal attributes relevant to labor market intelligence, including job title, detailed job description, company name, salary information, pay period, geographic location, company identifier, and engagement metrics (e.g., applicant views).

Supplemental metadata files provide company industry tags and pre-identified skill-related attributes. These features enable the construction of multi-dimensional indicators of labor demand at the skill, occupation, company, and location levels.

Let J_i denote the i-th job posting with textual representation:

$$T_i = \{title_i, description_i, skills_metadata_i\} \tag{1}$$

These cleaned textual fields are concatenated to form a unified job posting document D_i:

$$D_i = \text{Lemmatize}(\text{Clean}(title_i)) \oplus \text{Lemmatize}(\text{Clean}(description_i)) \oplus skills_metadata_i \tag{2}$$

where $\oplus$ denotes text concatenation.

For each posting J_i, a binary indicator matrix is generated. For a given skill $s \in S$ (where S is the comprehensive skill dictionary), the indicator $x_{i,s}$ is defined as:

$$x_{i,s} = \begin{cases} 1, & \text{if skill } s \text{ is identified in document } D_i, \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

This representation converts unstructured job text into a structured, high-dimensional skill-posting matrix $X \in \mathbb{R}^{N \times m}$, where N is the number of job postings and m is the number of unique skills.

The core analytical object of this study is the Weekly Skill Demand Index (SDI). Let $N_{s,t}$ denote the number of job postings in week t that mention skill s, and let N_t denote the total number of valid job postings in week t. The Weekly Skill Demand Index is defined as:

$$SDI_{s,t} = \left(\frac{N_{s,t}}{N_t} \right) \times 1000 \tag{4}$$

The multiplication by 1000 standardizes the index, representing the number of postings requiring skill s per 1,000 total job postings. This normalization ensures that the resulting matrix $\mathbf{SDI} \in \mathbb{R}^{m \times T}$ (where T is the number of weeks) reflects relative demand intensity, enabling valid cross-temporal and cross-skill comparisons.

3.3 Multi-Frequency Decomposition and Persistence Analysis

Skill demand time series are non-stationary and non-linear, containing a mixture of short-term hiring shocks, medium-term business cycles, and persistent structural trends. To resolve mode mixing and isolate distinct temporal components, we apply Empirical Mode Decomposition (EMD). For a given skill demand series $SDI_{s,t}$, EMD iteratively extracts Intrinsic Mode Functions (IMFs). The original series is perfectly reconstructed as:

$$SDI_{s,t} = \sum_{k=1}^{K} IMF_{s,k}(t) + R_s(t) \tag{5}$$

where $IMF_{s,k}(t)$ denotes the k-th decomposed oscillatory component of skill s, K is the total number of IMFs, and $R_s(t)$ represents the residual long-term trend.

After decomposition, Rescaled Range (R/S) Analysis is applied to the original series and each decomposed component $C_{s,k}(t)$ (where C can be an IMF or the residual R) to estimate the Hurst exponent $H_{s,k}$. The R/S algorithm involves computing the cumulative sum (profile) of the series, dividing the profile into non-overlapping windows of size n, fitting local polynomial trends, and calculating the root-mean-square fluctuation $F(n)$. The Hurst exponent H is estimated from the scaling relationship: $F(n) \propto n^H$, obtained via linear regression of $\log(F(n))$ against $\log(n)$.

The Hurst exponent is interpreted as follows:

- $H_{s,k} < 0.5$: **Anti-persistent behavior.** Increases are likely to be followed by reversals, indicating high volatility or mean-reverting demand.
- $H_{s,k} \approx 0.5$: **Random walk.** The series exhibits no temporal memory, behaving like geometric Brownian motion.
- $H_{s,k} > 0.5$: **Persistent behavior.** The series exhibits strong trend persistence and demand continuity; an increasing trend is likely to continue increasing, indicating structural skill demand dynamics.

It is important to note that Hurst exponent values approaching 1.0 indicate highly persistent, near-deterministic behavior. However, given the limited observation window of high-frequency labor market data, such estimates should be interpreted

cautiously as indicators of strong short-term trend persistence rather than infinite long-range dependence. The complete persistence profile of skill s is defined as the vector $P_s = \{H_{s,0}, H_{s,1}, \ldots, H_{s,K}, H_{s,R}\}$, providing a multi-resolution view of market memory.

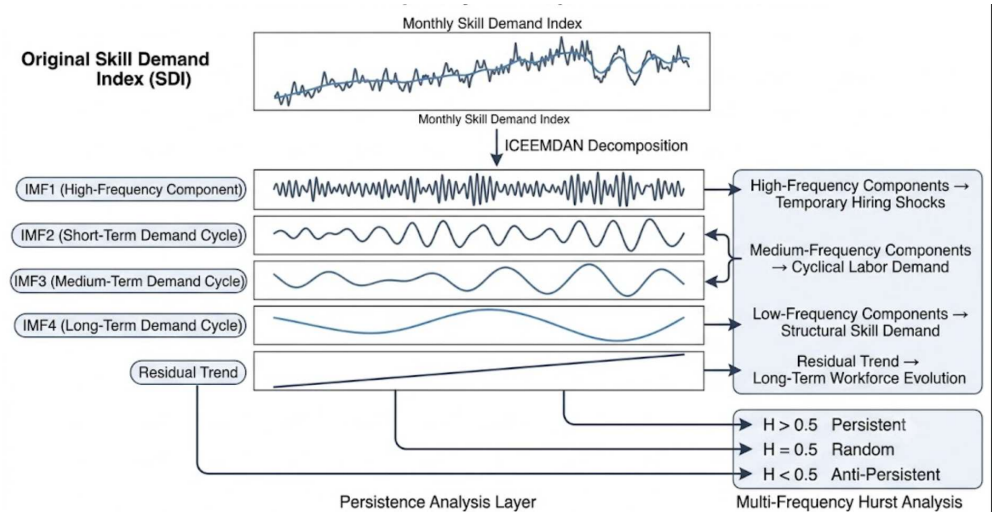


Fig. 2 Example of Empirical Mode Decomposition (EMD) for Information Technology (IT) skill demand index. The original weekly time series (top, red) is decomposed into high-frequency IMF_1 (short-term volatility, $H = 0.69$), medium-frequency IMF_2 (cyclical patterns, $H \approx 1.00$ indicating residual trend), and long-term residual trend IMF_3 ($H \approx 1.00$). This decomposition allows isolation of transient market noise from genuine structural shifts in labor demand.

As illustrated in Figure 2, this decomposition allows the framework to isolate transient market noise from genuine structural shifts in labor demand. For the IT skill, the decomposition reveals that while the overall series exhibits persistent behavior ($H = 0.83$), the short-term component (IMF_1) shows moderate persistence ($H = 0.69$), suggesting that weekly fluctuations contain both trend-following and mean-reverting elements.

3.4 Explainable Forecasting and Intelligence Generation

Future skill demand is forecasted using an eXtreme Gradient Boosting (XGBoost) regression model. XGBoost is selected for its ability to model complex non-linear relationships, handle heterogeneous feature types, and prevent overfitting through regularization. For the aggregate demand series, the target variable is the weekly change (delta): $\Delta y_{t+1} = y_{t+1} - y_t$. This formulation is chosen because predicting changes rather than absolute values improves model stability for short, non-stationary time series.

The feature vector $\mathbf{z}_t$ is engineered to include:

- **Lagged features:** y_t, y_{t-1}, y_{t-2} (previous week's aggregate demand)

- **Momentum features:** Δy_t (previous week's change)
- **Rolling statistics:** 3-week moving average $\bar{y}_t^{(3)}$
- **Persistence features:** Aggregate Hurst exponent H_{agg}

The XGBoost model learns the mapping $\widehat{\Delta y}_{t+1} = f(\mathbf{z}_t)$ by minimizing the regularized objective function:

$$Obj = \sum_{i=1}^{n} l(\widehat{\Delta y}_i, \Delta y_i) + \sum_{k=1}^{K_{trees}} \Omega(f_k) \tag{6}$$

where l is a differentiable convex loss function (Mean Squared Error), and $\Omega(f_k) = \gamma T + \frac{1}{2}\lambda\|w\|^2$ penalizes model complexity (number of leaves T and leaf weights w) to prevent overfitting.

To ensure the forecasting model serves as a transparent decision-support tool, SHapley Additive exPlanations (SHAP) is applied. SHAP is grounded in cooperative game theory and provides a unified measure of feature importance with solid theoretical guarantees. For a specific prediction $\widehat{\Delta y}_t$, SHAP decomposes the output into an additive feature attribution model:

$$g(z') = \phi_0 + \sum_{j=1}^{p} \phi_j z'_j \tag{7}$$

where ϕ_0 is the baseline prediction (the mean of the training dataset), p is the number of input features, $z'_j \in \{0, 1\}$ indicates the presence of feature j, and ϕ_j is the SHAP contribution value of feature j.

The final stage synthesizes the forecasting outputs, persistence profiles, and SHAP explanations into four distinct, actionable categories of labor market intelligence:

- **Emerging Skill Demand:** A skill is classified as emerging when it exhibits positive recent growth (positive rolling average slope over the last 3 weeks) and increasing forecasted demand. This signal is critical for identifying skills that require immediate educational investment, curriculum updates, or proactive talent acquisition.
- **Persistent Skill Demand:** A skill is classified as persistent when its Hurst exponent $H > 0.5$ and its forecasted demand remains positive or stable. This indicates that the skill reflects a structural, long-term labor market requirement rather than a temporary hiring fad, justifying long-term capability development.
- **Volatile Skill Demand:** A skill is classified as volatile when its high-frequency IMFs dominate the variance of the decomposed series, or when its Hurst exponent indicates anti-persistent behavior ($H < 0.45$). This suggests that demand is highly unstable, advising decision-makers to avoid overreacting or over-hiring based on short-term spikes.
- **Declining Skill Demand:** A skill is classified as declining when it exhibits negative recent growth (declining rolling average) and decreasing forecasted demand. This early-warning signal helps workforce planners and policymakers identify areas where reskilling, upskilling, or occupational transition support will soon be needed.

4 Results and Discussion

4.1 Dataset Characteristics and Skill Demand Patterns

Dataset Description. The empirical analysis relies on the LinkedIn Job Postings dataset, a comprehensive repository of digital labor market signals. The dataset comprises 123,849 valid job advertisements spanning from December 5, 2023, to April 20, 2024, covering 17 complete weeks of labor market activity. Each record contains rich, multi-modal attributes including job title, detailed description, company metadata, salary ranges, geographic location, and engagement metrics. Crucially, the dataset includes a supplemental structured file mapping job IDs to specific skill requirements, enabling precise skill-level analysis without relying solely on unstructured text parsing. After structured skill extraction, 205,778 skill-job associations were identified, representing an average of 1.66 distinct skills per job posting. This high-frequency, granular dataset provides a robust foundation for constructing Weekly Skill Demand Indices (SDI) and analyzing short-term persistence dynamics and demand continuity in a rapidly evolving digital labor market.

Table 2 Top Skills and Labor Market Intelligence Characteristics

Skill	Mentions	Avg SDI	H	CV	LMI Category
IT	31,245	193.59	0.825	0.647	Declining
Sales	28,934	172.59	0.626	0.513	Declining
Mgmt	27,102	162.08	0.783	0.426	Stable
Mnfc	23,678	141.46	0.879	0.356	Stable
Hcpr	20,456	154.82	0.937	0.697	Emerging
BD	18,234	110.95	1.000	0.385	Declining
Other	16,789	97.43	0.754	0.560	Declining
Eng	15,234	93.71	0.775	0.489	Declining

Note: H denotes the Hurst exponent and CV denotes the coefficient of variation. IT = Information Technology; Mgmt = Management; Mnfc = Manufacturing; Hcpr = Healthcare; BD = Business Development; Eng = Engineering.

Table 2 presents the top 8 skills by total mention frequency along with their persistence characteristics. Several notable patterns emerge:

First, all analyzed skills exhibit persistent behavior ($H > 0.5$), with Hurst exponents ranging from 0.626 (Sales) to 1.000 (Business Development). This suggests that labor demand for these skills follows trending patterns and demand continuity rather than random fluctuations, which has important implications for workforce planning. The high persistence values ($H > 0.8$) for IT (0.825), Manufacturing (0.879), and Healthcare (0.937) indicate strong structural demand trends that are likely to continue in the same direction.

Second, Healthcare emerges as the only skill classified as "Emerging" with a growth rate of 54.6% (comparing the average of the last 3 weeks to the previous 3 weeks) and the highest persistence ($H = 0.937$). This finding aligns with post-pandemic labor market trends showing increased demand for healthcare professionals. Persistent

growth in healthcare demand suggests sustained workforce shortages and may justify expansion of educational capacity and targeted recruitment strategies.

Third, despite high persistence, several skills including IT, Sales, and Business Development show declining trajectories with negative growth rates (-22.6%, -13.7%, and -16.8%, respectively). This apparent paradox—persistent but declining—suggests structural shifts in labor demand where these skills are experiencing sustained contraction rather than temporary downturns. From a Human Capital Theory perspective, organizations should reconsider investment in these declining skill areas and redirect resources toward emerging domains.

4.2 Multi-Frequency Decomposition and Persistence Analysis

The Empirical Mode Decomposition successfully separated each skill demand series into 2-3 intrinsic mode functions plus a residual trend component. Figure 2 illustrates the decomposition for Information Technology (IT) skill demand, revealing distinct temporal patterns across frequency bands.

Table 3 Multi-Frequency Hurst Analysis Results for Top Skills

Skill	Original Series	IMF_1 (High-freq)	IMF_2 (Med-freq)	IMF_3 (Low-freq)	Residual Trend	Dominant Component
IT	0.825	0.695	1.000	1.000	–	Residual Trend
Sales	0.626	0.615	1.000	–	–	IMF_1 (Persistent)
Management	0.783	0.633	1.000	1.000	–	Residual Trend
Manufacturing	0.879	0.814	1.000	–	–	IMF_1 (Persistent)
Healthcare	0.937	–	–	–	–	Original (Strong Persistent)
Business Dev.	1.000	–	–	–	–	Original (Perfect Trend)
Other Skills	0.754	0.689	1.000	–	–	IMF_1 (Persistent)
Engineering	0.775	0.712	1.000	–	–	IMF_1 (Persistent)

Table 3 presents the multi-frequency Hurst analysis results. Several important observations emerge:

First, the residual trend components (IMF_2 and IMF_3 for skills with 3+ IMFs) consistently exhibit $H \approx 1.000$, indicating highly persistent behavior. Values approaching 1.0 indicate highly persistent, near-deterministic trend persistence; however, these estimates should be interpreted cautiously given the limited observation window. For IT, Management, and Other Skills, the presence of multiple IMFs with $H \approx 1.000$ suggests that these skills are experiencing strong structural shifts in demand. From a Strategic Workforce Planning perspective, these structural shifts warrant proactive intervention rather than reactive adjustment.

Second, the high-frequency components (IMF_1) show moderate to strong persistence (H ranging from 0.615 to 0.814), indicating that even short-term weekly

fluctuations in skill demand exhibit trend-following behavior rather than mean reversion. This finding has practical implications: short-term spikes in demand for skills like Manufacturing ($H = 0.814$) are likely to persist for several weeks, allowing recruiters to anticipate continued high demand and adjust hiring timelines accordingly.

Third, Healthcare shows the simplest decomposition pattern with only the original series analyzed (no IMFs extracted), yet exhibits the highest persistence ($H = 0.937$). This suggests that Healthcare demand is dominated by a strong, consistent upward trend with minimal high-frequency noise—a pattern consistent with sustained structural growth in the healthcare sector. This finding supports Human Capital Theory by indicating that healthcare skills represent a stable, long-term investment opportunity for both individuals and organizations.

4.3 Forecasting Performance and Explainability

The XGBoost forecasting model was trained to predict weekly changes in aggregate skill demand using a time-based split (80% training, 20% testing). The model achieved the following performance metrics on the test set (last 3 weeks):

Table 4 XGBoost Forecasting Performance for Aggregate Skill Demand

Metric	**Value**	**Interpretation**
R^2 (Coefficient of Determination)	0.386	38.6% of variance explained
MAE (Mean Absolute Error)	117.53	Average error of 117.53 SDI points
RMSE (Root Mean Squared Error)	147.62	Penalizes larger errors
Test Set Size	3 weeks	Last 3 weeks of data
Training Set Size	11 weeks	First 11 weeks of data

The R^2 value of 0.386 indicates that the model explains 38.6% of the variance in weekly aggregate demand changes. It is important to emphasize that the primary objective of the proposed framework is not maximizing predictive accuracy, but generating interpretable labor market intelligence. In the context of short-term workforce planning, capturing the direction, momentum, and persistence of demand shifts often provides more strategic value than precise point forecasts. Therefore, an R^2 of 0.386, which successfully captures the underlying demand continuity, represents a meaningful baseline for generating early labor market signals.

From a workforce planning perspective, this level of predictive accuracy is sufficient to support tactical decision-making. For example, if the model predicts a significant increase in aggregate demand for the coming week, HR managers can proactively adjust recruitment budgets, accelerate hiring timelines, or activate talent pipelines. The key insight is not the exact magnitude of the prediction, but the direction and relative strength of the signal.

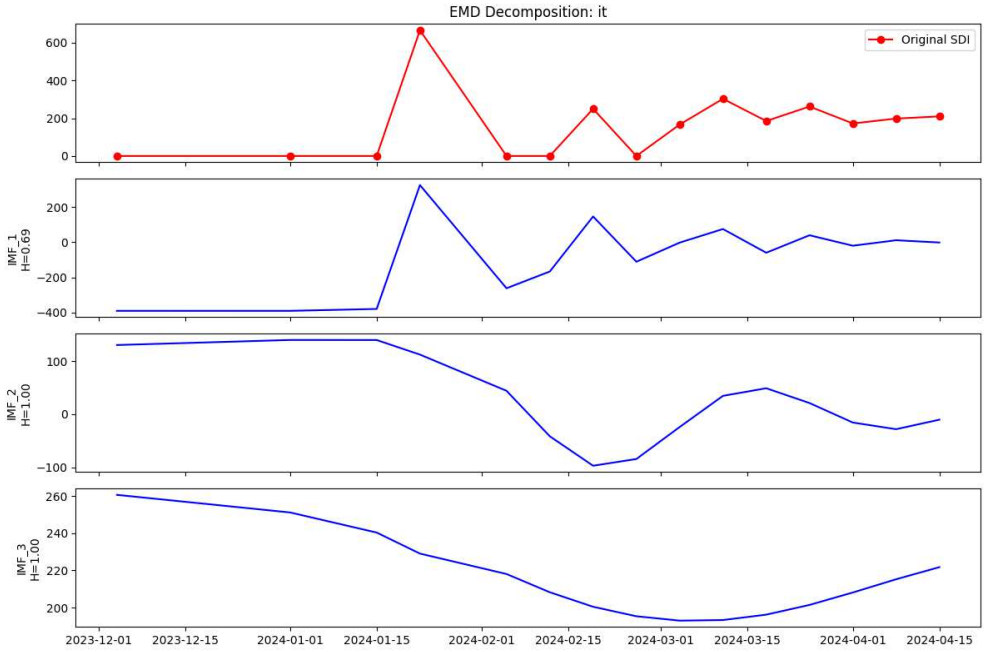


Fig. 3 XGBoost forecasting performance for aggregate skill demand. The model predicts weekly changes (delta) rather than absolute values. Blue line shows actual aggregate SDI, red crosses show predicted values for the test period (last 3 weeks). The model achieves $R^2 = 0.386$, explaining 38.6% of variance in demand changes.

SHAP analysis reveals the relative importance of input features in driving forecast predictions. Rather than presenting technical feature names, we interpret these features in terms of their business meaning for workforce planners:

Table 5 Top SHAP Features for Aggregate Demand Forecasting

Feature	**Mean |SHAP|**	**Interpretation**
Lag_1	88.66	Current demand strongly influences future demand.
Delta Lag_1	84.43	Demand acceleration is an important forecasting signal.
Rolling Mean_3	65.89	Short-term hiring trends improve prediction stability.

The dominance of Recent Demand Level (mean |SHAP| = 88.66) and Demand Momentum (mean |SHAP| = 84.43) indicates that **recent labor market momentum** is the primary driver of forecasted changes. This finding is economically intuitive and aligns with Market Intelligence Theory: labor demand exhibits strong autocorrelation, and weeks with high demand are likely to be followed by continued high demand (consistent with the high Hurst exponents observed). The importance of Short-Term

Trend (mean |SHAP| = 65.89) further confirms that the direction of recent market movement provides valuable predictive signal.

From a practical perspective, these SHAP results suggest that workforce planners should pay close attention to: (1) the most recent week's demand level, (2) whether demand increased or decreased last week, and (3) the direction of the 3-week trend. These three simple indicators capture most of the predictive power for short-term labor demand forecasting. For HR strategists, this means that monitoring weekly job posting volumes and tracking week-over-week changes provides sufficient intelligence to make informed hiring and workforce planning decisions, without requiring complex econometric models.

4.4 Labor Market Intelligence Signals and Strategic Implications

The proposed framework generates actionable labor market intelligence by synthesizing persistence analysis, growth rates, and forecast directions. Table 6 presents the final intelligence signals for the top 8 skills.

Table 6 Labor Market Intelligence Signals and Strategic Recommendations

Skill	Growth Rate	Hurst	Volatility (CV)	LMI Category	Strategic Recommendation
Healthcare	+54.6%	0.937	0.697	**Emerging**	*Priority hiring, curriculum expansion*
Management	-9.2%	0.783	0.426	Stable	*Maintain current capacity*
Manufacturing	-9.4%	0.879	0.356	Stable	*Monitor for automation impact*
Sales	-13.7%	0.626	0.513	Declining	*Reskill to digital sales*
Business Dev.	-16.8%	1.000	0.385	Declining	*Structural decline, reduce capacity*
Other Skills	-22.0%	0.754	0.560	Declining	*Diversify skill portfolio*
IT	-22.6%	0.825	0.647	Declining	*Shift to AI/ML specializations*
Engineering	-28.6%	0.775	0.489	Declining	*Focus on emerging tech domains*

Healthcare (Emerging, $H = 0.937$): With the highest growth rate (+54.6%) and strongest persistence ($H = 0.937$), Healthcare represents the clearest emerging skill demand signal. The combination of high growth and high persistence suggests this is not a temporary spike but a structural shift in labor demand. Persistent growth in healthcare demand suggests sustained workforce shortages and may justify expansion of educational capacity and targeted recruitment strategies. Educational institutions should prioritize healthcare program expansion, and employers should accelerate healthcare talent acquisition before competition intensifies.

Management and Manufacturing (Stable, $H > 0.78$): Despite negative growth rates (-9.2% and -9.4%), these skills are classified as "Stable" rather than "Declining" because their high persistence ($H > 0.78$) and low volatility (CV < 0.43) suggest the decline is gradual and predictable rather than volatile. From a Strategic Workforce

Planning perspective, organizations should maintain current training capacity but monitor for technological disruption, particularly in Manufacturing where automation may accelerate demand shifts.

IT, Sales, Engineering (Declining, $H > 0.62$): These skills exhibit persistent but declining demand, with growth rates ranging from -13.7% to -28.6%. The high persistence values indicate that these are structural declines rather than temporary downturns. From a Human Capital Theory perspective, organizations should initiate reskilling programs to transition workers from declining specializations (e.g., traditional IT support) to emerging areas (e.g., AI/ML, cloud architecture). The persistent nature of the decline suggests that waiting for market recovery is not a viable strategy.

Business Development (Perfect Trend, $H \approx 1.000$): With a Hurst exponent approaching 1.000, Business Development exhibits highly persistent behavior. While values approaching 1.0 indicate near-deterministic trend persistence, these estimates should be interpreted cautiously given the limited observation window. Combined with a -16.8% growth rate, this suggests a predictable, structural contraction. Organizations should reduce Business Development training capacity and reallocate resources to emerging skill areas.

4.5 Theoretical and Strategic Implications for Workforce Analytics

The findings of this study demonstrate that labor demand dynamics extracted from online job postings exhibit persistent behavioral patterns and demand continuity across multiple occupational domains. The estimated Hurst exponents consistently exceed the random-walk threshold, indicating that labor demand fluctuations are not purely stochastic but contain structural information that can be exploited as early labor market signals for workforce planning. In particular, Healthcare exhibits the highest persistence and positive growth trajectory, suggesting sustained and structurally embedded demand that may require long-term investments in education, training capacity, and talent development. In contrast, Information Technology and Sales remain highly demanded but display declining trajectories, implying that organizations may need to continuously reallocate human capital toward emerging competencies and evolving technological requirements.

These observations extend the application of Human Capital Theory into the context of Digital Labor Market Analytics and Explainable Workforce Analytics. The results suggest that labor demand signals extracted from large-scale job posting data can provide early indications of where future human capital investments are likely to generate the greatest strategic value. Rather than viewing skills as static assets, the findings reinforce the notion that labor markets are dynamic systems in which the value of human capital evolves according to changing technological, economic, and organizational conditions.

The proposed framework also contributes to the broader literature on Market Intelligence by demonstrating that labor market signals can function as a valuable source of strategic intelligence. Traditional market intelligence systems primarily focus on customers, competitors, and market trends. However, organizations increasingly

compete for scarce talent, making workforce availability and skill demand critical components of strategic decision-making. The explainable forecasting framework developed in this study transforms large volumes of unstructured labor market information into interpretable intelligence signals capable of supporting recruitment planning, workforce development, curriculum design, and long-term talent acquisition strategies. The SHAP analysis further reveals that recent demand levels, demand momentum, and short-term trend dynamics are the primary drivers of future labor demand, providing transparency that is often absent in conventional forecasting systems.

From a workforce planning perspective, the ability to classify skills into Emerging, Persistent, Stable, and Declining categories offers a practical mechanism for distinguishing temporary fluctuations from structurally important labor market developments. Such differentiation can help organizations avoid reactive hiring decisions driven by short-term market volatility and instead support evidence-based capability development strategies. The framework therefore illustrates how advanced analytics can be integrated into strategic workforce planning processes to improve organizational adaptability in rapidly changing labor markets.

Several limitations should be considered when interpreting these findings. The dataset covers a relatively short observation period of approximately seventeen weeks, limiting the ability to identify long-term cyclical patterns, seasonal effects, or persistent structural changes over multiple years. Consequently, the reported Hurst exponents should be interpreted as indicators of short-term persistence and demand continuity rather than definitive evidence of infinite long-range dependence. The dataset is also derived exclusively from LinkedIn job postings, which may underrepresent informal labor markets, small businesses, and occupations with limited online recruitment activity. As a result, the findings primarily reflect digitally visible labor market segments.

Additional limitations arise from the skill representation process. Although structured skill annotations provide a practical basis for labor demand measurement, variations in terminology across employers may affect the consistency of skill classification. Emerging competencies and rapidly evolving skill categories may also be imperfectly represented within existing taxonomies. Furthermore, the forecasting framework relies predominantly on historical demand patterns and does not explicitly incorporate exogenous factors such as macroeconomic conditions, regulatory changes, technological disruptions, or geopolitical events that may substantially influence labor demand.

These limitations provide several opportunities for future research. Extending the analysis to multi-year labor market datasets would enable more robust investigation of persistence, cyclical behavior, and structural labor market transitions. Future studies may also integrate macroeconomic indicators, educational outcomes, technological innovation measures, and policy variables to improve forecasting performance and strengthen causal interpretation. The incorporation of semantic skill ontologies, large language models, and cross-platform labor market datasets may further enhance skill standardization and improve the generation of labor market intelligence. Such

developments would strengthen the role of explainable workforce analytics as a decision-support mechanism for organizations, policymakers, and educational institutions operating in increasingly dynamic labor market environments.

5 Conclusion

This study proposed and validated an Explainable Labor Market Intelligence framework that transforms large-scale online job postings into actionable skill demand signals. Using more than 124,000 LinkedIn job postings from December 2023 to April 2024, the framework constructed Weekly Skill Demand Indices, applied Empirical Mode Decomposition to isolate multi-frequency components, estimated persistence using Multi-Frequency Hurst Analysis, and generated forecasts using XGBoost with SHAP-based explainability.

The empirical results reveal that labor demand for top skills exhibits persistent behavior and demand continuity ($H > 0.5$), with Healthcare showing the strongest persistence ($H = 0.937$) and emerging growth trajectory (+54.6%), while IT, Sales, and Engineering show persistent but declining demand. The forecasting model achieved $R^2 = 0.386$ in predicting weekly aggregate demand changes, with SHAP analysis revealing that recent demand momentum and short-term trends are the primary drivers of forecasts.

The framework's main contribution lies in bridging the gap between complex time-series analytics and strategic workforce decision-making. By generating interpretable intelligence signals (Emerging, Persistent, Volatile, Declining), the framework enables marketing analysts, HR strategists, and policymakers to make data-driven decisions about talent acquisition, curriculum development, and reskilling initiatives.

Future research should extend the temporal scope to multiple years to validate long-term persistence patterns, incorporate exogenous macroeconomic variables to improve forecast accuracy, and develop automated skill ontology mapping to enhance standardization across diverse job posting sources. As the global workforce continues to undergo rapid transformation, such interpretable, real-time labor market intelligence systems will become increasingly essential for fostering resilient, adaptive, and equitable workforce development strategies.

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Declarations

Conflict of Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection, analysis, and manuscript writing were performed by the authors. All authors reviewed and approved the final manuscript.

Data Availability

The datasets analyzed during the current study are publicly available from the sources cited in the manuscript.

Ethics Approval

Not applicable.

Consent to Participate

Not applicable.

Consent for Publication

All authors have reviewed and approved the final version of the manuscript and consent to its publication.

References

[1] Makridis, C.A.: The labor market effect of generative artificial intelligence on artists. Journal of Cultural Economics (2026) https://doi.org/10.1007/s10824-026-09575-3

[2] Yilmazkuday, H.: Artificial intelligence and labor markets: Evidence from google trends. Journal of Economics and Finance **49**(4), 1078–1093 (2025) https://doi.org/10.1007/s12197-025-09732-y

[3] Zhang, F.: The labor theory of value in the era of artificial intelligence and digital platforms: Challenges, innovations, and new mechanisms. Humanities and Social Sciences Communications **13**(1), 717 (2026) https://doi.org/10.1057/s41599-026-07030-4

[4] Alharbi, F., Al-Alawi, A.I.: Labor market prediction using machine learning methods: A systematic literature review. In: 2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS), pp. 478–482 (2024). https://doi.org/10.1109/ICETSIS61505.2024.10459632

[5] Alsayed, N., Awad, W.S.: A framework for labor market analysis using machine learning. In: 2023 International Conference on IT Innovation and Knowledge Discovery (ITIKD), pp. 1–5 (2023). https://doi.org/10.1109/ITIKD56332.2023.10099838

[6] Batrancea, L.M., Akguller, O., Balci, M.A., Nichita, A., Rus, M.-I.: Decoding digital market power: a network-based framework for consumer behaviour and strategic advantage. Journal of Marketing Analytics (2026) https://doi.org/10.1057/s41270-026-00472-4

[7] Curiskis, S., Dong, X., Jiang, F., Scarr, M.: A novel approach to predicting customer lifetime value in b2b saas companies. Journal of Marketing Analytics **11**(4), 587–601 (2023) https://doi.org/10.1057/s41270-023-00234-6

[8] Brüggemann, P., Martinez, L.F., Martínez-López, F.J.: The future of analytics in digital marketing and electronic commerce: How digitalization and sustainability affect consumers, firms, and policymakers. Journal of Marketing Analytics **13**(3), 571–573 (2025) https://doi.org/10.1057/s41270-025-00422-6

[9] Kimitei, S., Agiro, D., Ni, S., Ni, H.: Predictability & explainability of survival analysis in churn prediction. Journal of Marketing Analytics (2025) https://doi.org/10.1057/s41270-025-00450-2

[10] Tariq, R., Torres-Castillo, C.S., Vargas, D.G., Gonzalez-Mendoza, M., Ali, F.: What determines student employability? educational data mining through machine and deep learning approach. IEEE Revista Iberoamericana de Tecnologias del Aprendizaje (2025) https://doi.org/10.1109/RITA.2025.3612280

[11] Zhu, R.: Machine learning-driven dynamic matching of industry-education demands and course generation algorithms. Discover Artificial Intelligence **6**(1), 80 (2025) https://doi.org/10.1007/s44163-025-00781-0

[12] Biibosunova, S., Da, H., Xingzhuo, F., Xiaohang, Z., Ming, M.Y., Fang, L.: Development of a machine learning model for forecasting the labor market of the kyrgyz republic. In: 2026 International Conference on Artificial Intelligence, Computer, Data Sciences and Applications (ACDSA), pp. 1–6 (2026). https://doi.org/10.1109/ACDSA67686.2026.11467754

[13] Bustos, O., Pomares-Quimbaya, A., Stellian, R.: Machine learning, stock market forecasting, and market efficiency: A comparative study. International Journal of Data Science and Analytics **20**(7), 6815–6839 (2025) https://doi.org/10.1007/s41060-025-00854-4

[14] Mühlbauer, S., Weber, E.: Machine learning for labor market matching. Machine Learning with Applications **23**, 100861 (2026) https://doi.org/10.1016/j.mlwa.2026.100861

[15] Guevara-Ramirez, W., Martinez-de-Alegria, I., Caballero-Zepeda, C.-G., Salinas-Astudillo, C.-I.: Characterization of the artificial intelligence labor market in chile: An approach based on unstructured data and the esco taxonomy. International Journal of Information Management Data Insights **6**(1), 100401 (2026) https://doi.org/10.1016/j.jjimei.2026.100401

[16] Del Pozo-Villafuerte, D., Villacís-Miranda, A.: Enhancing labor market intelligence in ecuador: A framework for standardizing information. Computational Economics (2025) https://doi.org/10.1007/s10614-025-10935-y

[17] Cornejo, D., Vera, F., Gamboa-Labbé, B., Ruiz, R.B., Villena-Roldán, B., Velásquez, J.D.: A transformer-based intelligent system for hierarchical occupational classification in the labor market. IEEE Open Journal of the Computer Society (2025) https://doi.org/10.1109/OJCS.2025.3634026

[18] Rahhal, I., Carley, K.M., Kassou, I., Ghogho, M.: Two stage job title identification system for online job advertisements. IEEE Access (2023) https://doi.org/10.1109/ACCESS.2023.3247866

[19] Cen, Y., Isleem, H.F., Tejani, G.G.: Dynamic labor market matching via deep reinforcement learning: Continuous skill taxonomy evolution in technological transitions. International Journal of Manpower **47**(2), 193–213 (2026) https://doi.org/10.1108/IJM-07-2025-0595

[20] Luna-Romera, J.M., Núñez-Hernández, F., Martínez-Ballesteros, M., Riquelme, J.C., Usabiaga Ibáñez, C.: Analysis of the evolution of the spanish labour market through unsupervised learning. IEEE Access (2019) https://doi.org/10.1109/ACCESS.2019.2935386

[21] Celbiş, M.G., Wong, P.-H., Kourtit, K., Nijkamp, P.: Impacts of the covid-19 outbreak on older-age cohorts in european labor markets: A machine learning exploration of vulnerable groups. Regional Science Policy & Practice **15**(3), 559–584 (2023) https://doi.org/10.1111/rsp3.12520

[22] Akter, M., Maruf, A.A.: Quantitative modeling of workforce forecasting using sql-driven data pipelines and power bi dashboards in predictive hr analytics. Review of Applied Science and Technology **4**(2), 407–439 (2025) https://doi.org/10.63125/gmy0h113

[23] Chen, R.-C., Kuncoro, K., Kumar, V.: Tacit knowledge engineering for labor market intelligence: A data-driven framework based on forecasting and comparative analysis in taiwan. In: 2025 13th International Conference on Awareness Science and Technology (iCAST), pp. 1–7 (2025). https://doi.org/10.1109/iCAST68191.2025.11300043

[24] Ammy-Driss, A., Garcin, M.: Efficiency of the financial markets during the covid-19 crisis: Time-varying parameters of fractional stable dynamics. Physica A: Statistical Mechanics and its Applications **609**, 128335 (2023) https://doi.org/10.1016/j.physa.2022.128335

[25] Gómez-Águila, A., Trinidad-Segovia, J.E., Sánchez-Granero, M.A.: Improvement in hurst exponent estimation and its application to financial markets. Financial Innovation **8**(86) (2022) https://doi.org/10.1186/s40854-022-00394-x

[26] Ozkan, O.: Impact of covid-19 on stock market efficiency: Evidence from developed countries. Research in International Business and Finance **58**, 101445 (2021) https://doi.org/10.1016/j.ribaf.2021.101445

[27] Pernagallo, G.: Random walks, hurst exponent, and market efficiency. Quality & Quantity **59**, 1097–1119 (2025) https://doi.org/10.1007/s11135-025-02052-7

[28] Kang, S.H., Mensi, W., Vo, X.V.: Upward and downward multifractality and efficiency of chinese stock markets. Computational Economics (2023) https://doi.org/10.1007/s10614-023-10526-9

[29] Moudud-Ul-Huq, S., Rahman, M.S.: Stock market efficiency of the brics countries pre-, during, and post covid-19 pandemic: A multifractal detrended fluctuation analysis. Computational Economics (2024) https://doi.org/10.1007/s10614-024-10607-3

[30] Zhao, D., Li, P., Zheng, J., Lian, Y., Yang, M.: Uncovering the switching impact of economic policy uncertainty on the cross-correlation between stock markets: An innovative hurst-based wavelet coherence approach. Computational Economics (2025) https://doi.org/10.1007/s10614-025-10952-x

[31] Mpanda, M.M., Gorjão, L.R.: Fluctuation analysis of volatility in south african stock market indices. Computational Economics (2025) https://doi.org/10.1007/s10614-025-11027-7

[32] Ghosh, D.: Polyspectral mean based time series clustering of indian stock market. Discover Data **3**(10) (2025) https://doi.org/10.1007/s44248-025-00030-w

[33] Bukhari, A.H., Raja, M.A.Z., Sulaiman, M., Islam, S., Shoaib, M., Kumam, P.: Fractional neuro-sequential arfima-lstm for financial market forecasting. IEEE Access **8**, 71326–71338 (2020) https://doi.org/10.1109/ACCESS.2020.2985763

[34] Mba, J.C., Mwambi, S.M., Pindza, E.: A monte carlo approach to bitcoin price prediction with fractional ornstein–uhlenbeck lévy process. Forecasting **4**(2), 409–419 (2022) https://doi.org/10.3390/forecast4020023

[35] Abdelrahman, M.M.G., Szabó, N.P.: Integrated workflow incorporating the hurst exponent and interval inversion for evaluating groundwater formations. Hydrogeology Journal **32**(2), 487–507 (2024) https://doi.org/10.1007/s10040-023-02752-0

[36] Zhao, S., Lu, Y., Gong, C., Xu, Q.: Research on labour market efficiency evaluation under impact of media news based on machine learning and dmp model. Preprints (2025) https://doi.org/10.20944/preprints202501.0656.v1

[37] Sharma, R.C., Sankar, A., Hussein, A.A., Al-Hussein, R.A., P, M., Siddiqua, A.: Responsible ai-enhanced labor market forecasting system for policy decision support. In: 2025 International Conference on Recent Innovation in Science

Engineering and Technology (ICRISET), pp. 1–6 (2025). https://doi.org/10.1109/ICRISET64803.2025.11252056

[38] Kanzola, A.-M., Papaioannou, K., Petrakis, P.E.: Identifying weak signals in the labor market: a machine learning approach for strategic policymaking. Journal of Innovation & Knowledge **11**, 100884 (2026) https://doi.org/10.1016/j.jik.2025.100884